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Food prices and production in the aftermath of natural disasters: the case of Peru*

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Abstract

We empirically investigate the economic impact of natural disasters on food prices and production. We address the key issues of data aggregation and counterfactual biases. Our data set consists of regional information on prices and production for fourteen food products in Peru. This granularity level of the data allows us to disentangle nominal from real effects, while we still can account for within-country differences. On the other hand, the random nature of intense rainfalls and droughts allows us to establish a natural counterfactual for each event by comparing between and within-regions. Our empirical results show that prices increase in the aftermath of disasters, while production strongly declines, which mask the price increases at the macroeconomic level. This is particularly apparent during extreme events. The supply channel turns out to be the main mechanism through which disasters affect prices. These effects are mostly heterogeneous. When conditioning on storage life-duration of the products, we find that prices of perishable products are affected by rainfalls only while those of semi-durable products by both rainfalls and droughts.

Key words: Climate events, price, production, fixed effects panel data, difference-in-differences.

JEL codes: C33, E20, Q54.

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1 Introduction

The economic implications of natural disasters have mostly been studied at the country level, with information being collected at a yearly frequency and on a nominal basis. To establish causal effects by means of country and nominal variables, much focus has been given to the use and construction of synthetic counterfactuals which have been hardly satisfactory (Cavallo et al., 2013; Barrios et al., 2010; Fomby et al., 2013). We contribute to the literature by (*i*) documenting a data set of natural disasters, prices and production for fourteen food products in Peru, and (*ii*) by presenting the effects of intense rainfalls and droughts on prices and production for food products in Peru. The prices and production of 14 food products are recorded at a monthly frequency between the years 2003 and 2018, for 24 regions. The time series dimension of the data set allows us to disentangle real from nominal effects. Given that climate events do not materialize simultaneously in every region, and neither take place every month, natural counterfactuals emerge from the data to measure the causal effects of intense rainfalls and droughts, simply by comparing events between and within regions.

The cross-country evidence reveals that the occurrence of natural disasters is associated with a decline in economic growth (Felbermayr and Gröschl, 2014; Klomp and Valckx, 2014; Botzen et al., 2019), with large disaster events having a significant economic impact (Fomby et al., 2013). However, these studies suffer from two key empirical shortcomings: (i) data aggregation, and (ii) counterfactual biases. First, macroeconomic variables are reported in nominal basis, which prevents the policy maker to disentangle price from quantity effects. Aggregate price indexes are estimated to increase during natural disasters (Klomp, 2020), which could partially offset the decline on real production. This is particularly relevant when analyzing moderate events that may not cause a major production disruption. As an illustration, El Niño Southern Oscillations (ENSO) is estimated to explain 20 percent of the world commodity prices movements (Brenner, 2002). In addition, the aggregate country information could mask important geographic asymmetric effects and, as a result, could bias down the macroeconomic impacts (Damania et al., 2020). Second, in the absent of a natural counterfactual, the cross-country regressions are unable to capture the unbiased effect of disasters. Ideally, we should aim at calculating the differences between the hypothetical and observed trends before and after the disaster, respectively. However, to construct a counterfactual, we need to select countries (or regions) with the same conditions as those for the country of interest. Such selections are difficult and can be criticized easily. A recent attempt based on using synthetic controls is presented in Cavallo et al. (2013).

We address these two empirical problems by exploiting a detailed price and production panel data set for fourteen products, with price and supply information at a subnational (region) level. In addition, we consider the two climate events of intense rainfalls and droughts which both materialize randomly and independently in each region. As an example, in March 2003, severe rainfalls occurred in the Amazon, while no event was registered in the Northern regions of Peru. In this case it is appropriate to make comparison between regions. As another example, intense rainfalls only occur in the Northern regions of Peru every four to six years. In this case we can consider within-region comparisons. For these purposes, we analyse the data simultaneously in a panel model setting where region-, product- and time-specific fixed effects are included.

A related study of Cavallo et al. (2014) considers supermarket prices and product availability information at the national level. It finds that prices remained relatively stable in the aftermath of the 2010 earthquake in Chile and the 2011 earthquake in Japan, despite the fact that product availability dropped significantly. This price stability result is then attributed to the *consumer anger* hypothesis of Rotemberg (2002): consumer anger refers to the situation where consumers care about the fairness of prices and, consequently, they react negatively to "unfair" price increases. The higher granularity level of our data set allows us to measure the intensity of events at a continuous scale, from moderate to extreme events. In addition, the data set provides price and production (supply) information at the subnational (region) level, from which an accurate picture emerges of the economic dynamics across the regions of Peru.

We formulate a panel data model for this data set and estimate its parameters using standard fixed effect estimation methods. Our main finding is that price increases in the aftermath of natural disasters, while the size of price increases depend on the storage life (duration) of the products. More specifically, we find that perishable products are affected only by heavy rainfall events and their prices are affected after four to six months. Further, semi-durable products are affected by both rainfall and drought events. The price increases due to rainfall are short-lived while these effects due to droughts take a longer time. The significant price increases are accompanied by a strong and significant decline in production. The decreases in the supply of products will most likely mask the price increases when data is studied at the aggregate level. When the model controls for changes in production, there is no longer a significant effect of disasters on prices. This result points out that the supply channel provides the main mechanism through which disasters affect prices. Our findings are robust against different model specifications that (i) allow for regional and product heterogeneous effects, (ii) consider correlated unobservable factors explaining both prices and production, and (iii) include individual monthly effects of disasters over time. Finally, we provide empirical evidence that extreme rainfall events lead to a stronger decline in production but also to substantial increase in prices.

The remainder of the paper is organized as follows. Section 2 briefly discusses the economic implications of rainfalls and droughts. Section 3 describes our price and production data set of Peru. The main empirical results are discussed in Section 4. Section 5 concludes.

2 Rainfalls and droughts

According to the World Bank Peru development report, the cost associated with intense rainfalls, droughts, earthquakes, landslides, and frost have amounted, on average to USD

40 million per year between 2003 and 2019.[1] Peru is particularly vulnerable to intense rainfall events, mainly due to El Niño Southern Oscillations. The geographical location of Peru is on the tropical west coast of South America where many regions are exposed to El Niño oscillations, which are characterized by prolonged, torrential rains. The World Bank documents that the El Niño event in 2017 has resulted in losses of USD3.1 billion, equivalent to 1.6 percent of the Peruvian gross domestic product (GDP). On the other hand, climate change and increasing temperature levels have intensified the occurrence of drought events in Peru, mostly in the southeast regions. In particular, droughts have become more frequent and lasting for longer periods in the southern area of the Andes, compromising the hydropower energy generation in the country. The absence of rain in this part of the country is mainly due to the La Niña phenomenon, also related to El Niño.

In Peru, the National Institute of Defense against Disasters (INDECI) plays a critical role in the systematic collection and analysis of data concerning natural disasters, along with their associated economic and social impacts. INDECI classifies rainfalls as disasters when a meteorological phenomenon results in more than 60 millimeters of precipitation within one hour. In contrast, droughts are characterized by a significant absence of precipitation over an extended period and can be further classified into two categories: absolute and partial. An absolute drought occurs when no rainfall exceeding 1 millimeter is recorded over a period of 15 consecutive days, while a partial drought is defined as a period of 29 consecutive days during which the average daily rainfall does not surpass 0.5 millimeters. Notably, INDECI does not differentiate between these types of droughts, instead categorizing them under a single classification.

Data on these phenomena is collected on a monthly basis, reflecting the dynamic and often unpredictable nature of natural disasters. INDECI provides comprehensive statistics regarding the number of individuals directly or indirectly affected by various disaster occurrences. In addition to these figures, the institute monitors other critical indicators, in-

[1] World Bank Group. 2022. Peru Country Climate and Development Report. CCDR Series.

cluding damage to households, agricultural land, and infrastructure. While these indicators are essential for understanding the intensity of disaster events, their informative capacity is constrained by the absence of associated monetary costs. This lack of financial context limits the ability to fully comprehend the economic implications of disasters. Furthermore, there is limited information on the stock of households and agricultural land at the subnational level, hindering a thorough assessment of the magnitude and scale of the shocks inflicted by natural disasters. Nevertheless, information regarding the total population residing in each region allows for the approximation of disaster intensity by comparing the number of affected individuals to the total population of that region.

The categorization of affected individuals is nuanced and multifaceted. It includes those who experience material or health disruptions as a result of disaster events, as assessed by INDECI during emergency response operations. Notably, the institute distinguishes between individuals who lack the financial resources to recover from such disruptions, thereby necessitating government assistance, and those who possess the means to navigate the aftermath independently. This differentiation is crucial for understanding the socio-economic ramifications of disasters, as it aids in identifying particularly vulnerable populations. Additionally, the data collected encompasses fatalities and individuals reported as missing, which serve as critical indicators of disaster severity, especially in the context of extreme weather phenomena such as El Niño. The availability of this information across all subnational regions enables a comprehensive view of climate intensity, facilitating easy comparison with the total population.

Since 2003, INDECI has systematically collected this information at the subnational level, allowing for a granular understanding of the impacts of disasters across different regions of Peru. In this paper, we employ the ratio of affected individuals to the total population in a given region as a metric for approximating disaster intensity.

2.1 A measure of climate disasters

The proxy climate disaster variable (in percentage) is defined as

$$x_{j,t}^{(s)} = 100 \times \frac{D_{j,t}^{(s)}}{N_{j,t}}, \tag{1}$$

where $D_{j,t}^{(s)}$ is the number of affected people due to the natural disaster s occurred in region j at time t, while $N_{j,t}$ is the total population in region j at time t.

Tables 1 and 2 summarize the main statistics for rainfalls and droughts events during the 2003-2018 period. Droughts have affected, on average, a larger proportion of people when compared to intense rainfalls, despite that intense rainfalls occur more often than droughts. The occurrence of rainfalls is not directly associated with its impact. For instance, rainfalls in the Amazonas region have occurred two times more than in any other region, but the average percentage of people affected by each event in the Amazonas is less than half compared to the rest of the country.

The occurrences of rainfalls and droughts do not necessarily overlap during the year. While rainfalls mostly occur between January and April, droughts mainly take place between October and January. If anything, rainfalls are preceded by droughts. In addition, there is hardly any overlap between regions affected by the same event. Notice that the regions in Peru are as large as many European countries. For example, the Loreto region is as large as Germany and the historical region of Cusco has the size of Ireland. Peru is the 19th largest country in the world, and the third largest in South America. Hence, it is unlikely that a single disaster has an impact on multiple regions.

2.2 Measuring the intensity of climate events

Ideally, analyses of climate disasters should incorporate variables that directly reflect the intensity of climatic events. For instance, precipitation data, particularly deviations from historical averages, serves as a more precise indicator of rainfall events. Similarly, deviations in average temperatures are more effective for capturing episodes of drought. However, detailed subnational data for these variables is only publicly available on an annual basis, which limits our ability to analyze the monthly impact of climate variations on prices and other economic factors.

In this paper, we utilize the number of people affected by disasters as a proxy variable; however, this approach presents certain challenges. For example, densely populated urban areas may report a higher number of affected individuals even during moderate climate events, simply due to population concentration. Moreover, limited access to healthcare services can exacerbate the reported number of affected individuals, thereby skewing the data.

To address these challenges, we estimate the conditional correlation between our proxy variable, the number of people affected by disasters relative to the total population in each region, and relevant climate variables (specifically, the average deviations from historical averages for precipitation and temperature) through simple regression analysis. We employ both ordinary least squares (OLS) and fixed effects panel regression models. This analysis is conducted on an annual basis, which inherently limits the number of observations. The results of this regression are summarized in Table 8 in the Appendix.

The relationship between our proxy variable and climate-related variables is estimated to be positive and significant, even when controlling for population density and access to healthcare services. Furthermore, the regression results indicate an R-squared value of nearly 30 percent for rainfall events and approximately 60 percent for droughts. These values suggest that a substantial portion of the variability in the number of individuals affected by disasters can be attributed to changes in climate conditions, thereby validating the use of our proxy variable for analyzing the impacts of climate events on prices.

Table 1: Descriptive statistics for the disaster events of rainfalls and droughts across the 24 regions in Peru, using the months from 2003 to 2018.

	Rainfall ($s = 1$)			Droughts ($s = 2$)		
Region j	Count	Average $x_{j,t}^{(1)}$	St.Dev.	Count	Average $x_{j,t}^{(2)}$	St.Dev.
Amazonas	172	0.06	0.131			
Ancash	88	0.15	1.059	4	7.42	13.425
Apurimac	158	0.51	1.915	21	4.25	7.882
Arequipa	68	0.41	0.740	7	0.05	0.016
Ayacucho	117	0.20	0.662	9	1.69	2.131
Cajamarca	152	0.09	0.687	1	0.00	0.000
Cusco	116	0.08	0.370	5	0.32	0.299
Huancavelica	140	0.33	1.113	22	1.53	4.492
Huanuco	123	0.18	0.746	7	0.55	1.278
Ica	31	0.70	1.237	4	0.99	1.768
Junin	97	0.03	0.057	2	2.89	4.077
La Libertad	74	0.33	2.209	1	0.00	0.000
Lambayeque	46	0.47	1.341	5	1.09	1.349
Lima	32	0.01	0.029	3	0.01	0.009
Loreto	18	0.04	0.082			
Madre de Dios	19	0.42	1.473	2	3.74	0.087
Moquegua	43	1.66	4.508			
Pasco	123	0.04	0.088	1	1.03	0.000
Piura	91	0.53	1.705	8	1.66	2.458
Puno	80	0.09	0.221	2	2.90	2.920
San Martin	78	0.08	0.226	5	0.16	0.238
Tacna	25	0.52	0.720	3	1.44	1.101
Tumbes	57	2.14	5.503	3	35.89	23.639
Ucayali	37	0.07	0.306	1	0.05	0.000
Average	83	0.38		6	3.22	

For the 24 regions in Peru in the first column, we report the number of events from 2003 to 2018 (Count), the sample average of the disaster variable $x_{j,t}^{(s)}$, defined in (1) and measured as a percentage, over the 192 months in the period from 2003 to 2018 (Average), for region j and disaster $s = 1, 2$, and the corresponding sample standard deviation (St.Dev.).

3 Data: prices and production

The database consists of unitary prices and production information for fourteen food items at regional level collected by the Peruvian national statistical agency (INEI).[2] Information is reported in the domestic currency, *Peruvian nuevos soles* ($\approx$ USD 0.25), and at a monthly

[2] Peru's National Institute of Statistics and Information

Table 2: Descriptive statistics for the disaster events of rainfalls and droughts for each month, using all 24 regions in Peru and all years from 2003 to 2018.

	Rainfall ($s = 1$)			Droughts ($s = 2$)		
Month	Count	Average $x_{j,t}^{(1)}$	St.Dev.	Count	Average $x_{j,t}^{(2)}$	St.Dev.
January	264	0.427	1.939	36	4.300	9.797
February	269	0.769	2.621	7	6.232	13.173
March	267	0.689	2.365	9	5.455	14.973
April	225	0.239	1.123	3	0.171	0.125
May	142	0.073	0.346	4	0.090	0.080
June	98	0.034	0.119	3	0.320	0.272
July	100	0.042	0.150	3	0.086	0.051
August	90	0.027	0.101	9	0.520	1.244
September	107	0.053	0.197	7	1.668	2.233
October	133	0.041	0.107	10	0.191	0.361
November	138	0.040	0.102	12	1.615	2.654
December	152	0.040	0.098	13	3.230	5.717

For each month, we report the number of events from 2003 to 2018 (Count), the sample average of the disaster variable $x_{j,t}^{(s)}$, defined in (1) and measured as a percentage, over all 24 regions and the 16 years from 2003 to 2018 (Average), for disaster $s = 1, 2$, and the corresponding sample standard deviation (St.Dev.).

basis for the period between 2003 and 2018. The food items are grouped into perishable and semi-durable products, which are determined by storage life duration under recommended conditions.[3] We consider perishable products those that can be stored up to six months, while semi-durable above that threshold.

Table 3 summarizes the prices and production statistics for the fourteen food items in the analysis. To facilitate the comparison between products, we calculate the standard deviation-to-average ratio, which is a broad representation of volatility within a product. The perishable products are more volatile than semi-durable products, but these volatility differences are non-significant. This may indicate that perishable products are more flexible than semi-durable products, and can therefore adjust to external shocks more quickly. Also, price volatility is correlated with production volatility (the correlation coefficient is 0.35).

Important to notice that the fourteen products considered in the analysis represent, nearly, fifty percent of the food consumer price index (CPI). The chicken, milk and rice

[3] Storage life information is obtained from the Food and Agriculture Organization (FAO) of the United Nations website.

items, already account by one third of the food price index. Therefore, the analysis stands relevant for understanding food inflation.

We consider food CPI, and product yearly crop yield as relevant control variables into the analysis. While there is not an individual CPI for all the food items in the sample, we consider 8 CPI group index that are further assigned to each individual food item. The groups (with the corresponding assigned items) are as follows: Fruit (Banana, Lemon, Orange, and Papaya), Sugar, Oil, Meat (Chicken), Milk & Eggs (Milk, and Egg), Tubers (Potato), Vegetables (Carrot, Garlic, and Onion), and Rice. On the other hand, the product crop yield variable is available at yearly basis for each food item in the sample, thus is matched to each month in a year. Both variables are collected by the Peruvian national statistical agency (INEI).

4 Empirical study

We discuss the design of our empirical study which focusses on the estimation of the impacts of natural disasters on food prices and production. The empirical estimation results are obtained from the two-way linear fixed effects panel regression framework which accommodates unobserved confounder factors within products and regions, and time-varying trends. Given that the disaster variable does not vary across products but only across regions, the standard errors can only be clustered at the regional level.

4.1 Empirical design

Our empirical study adopts the two-way linear fixed effects panel model, which can be represented in least squares dummy variable (LSDV) form as given by

$$\log p_{i,j,t} = \mu_{i,j} + \gamma_{i,t} + \theta_t + \sum_{\tau=0}^{3} \left(\beta_{1,\tau} x_{j,t,\tau}^{(1)} + \beta_{2,\tau} x_{j,t,\tau}^{(2)} \right) + \phi \log c_{i,j,t+12} + \epsilon_{i,j,t} \tag{2}$$

Table 3: Descriptive statistics for food prices and production from 2003 to 2018.

	Type	Prices (in sol, per kg.) Average	St.Dev.	Ratio	Production (per tn.) Average	St.Dev.	Ratio
Banana	Perishable	1.31	0.50	0.38	7528	9650	1.28
Carrot	Perishable	1.51	0.66	0.44	966	1916	1.98
Chicken	Perishable	7.75	1.77	0.23	3715	10648	2.87
Egg	Perishable	4.65	0.87	0.19	1069	2419	2.26
Lemon	Perishable	3.02	1.69	0.56	1031	2756	2.67
Milk	Perishable	2.49	0.34	0.14	5715	8124	1.42
Orange	Perishable	1.27	0.51	0.40	1824	4411	2.42
Papaya	Perishable	2.25	1.01	0.45	711	1304	1.83
Garlic	Semi-durable	7.10	3.20	0.45	657	2306	3.51
Oil	Semi-durable	6.11	1.02	0.17	2435	5599	2.30
Onion	Semi-durable	1.69	0.64	0.38	3500	8923	2.55
Potato	Semi-durable	1.13	0.40	0.36	18631	32886	1.77
Rice	Semi-durable	2.20	0.44	0.20	17365	31706	1.83
Sugar	Semi-durable	2.28	0.50	0.22	158715	140420	0.88
Average	Perishable	3.03	0.92	0.35	2820	5154	2.09
Average	Semi-durable	3.42	1.03	0.29	33551	36937	2.14

For each month, we report the sample average (Average), sample standard deviation (St.Dev) and the ratio of sample standard deviation against sample average (Ratio = St.Dev. / Average) for the prices (in Peruvian nuevos soles ≈ USD0.25) and production (in tonnes kilogram, tn.) for 14 products which can be classified as Perishable or Semi-durable. The averags of these statistics are also provided for the product groups of Perishable (8 products) and Semi-durable (6 products). We notice that the unitary price for Oil is determined in litters and for Milk in grains (410 gram).

where $p_{i,j,t}$ is the price (in levels or relative to overall food prices) of product $i = 1, \ldots, 14$, in region $j = 1, \ldots, 24$, and for monthly time index $t = 1, \ldots, 192$, with product/region effect $\mu_{i,j}$ (consisting of $14 \times 24 = 336$ coefficients), overall time effects θ_t (consisting of 168 coefficients due to the 24 periods absorbed by lags and forwards in the model specification), and product/time effect $\gamma_{i,t}$ (consisting of 14×192 coefficients), variable $x^{(s)}_{j,t,0}$ is a proxy for damages associated to rainfalls ($s = 1$) and droughts ($s = 2$) in region j at time t, $x^{(s)}_{j,t,1} = (x^{(s)}_{j,t-1,0} + x^{(s)}_{j,t-2,0} + x^{(s)}_{j,t-3,0})/3$ is the average of the past three months, representing the previous quarter (Q1), $x^{(s)}_{j,t,2} = (x^{(s)}_{j,t-4,0} + x^{(s)}_{j,t-5,0} + x^{(s)}_{j,t-6,0})/3$ is the average representing the quarter before last (Q2), $x^{(s)}_{j,t,3} = (x^{(s)}_{j,t-7,0} + \ldots + x^{(s)}_{j,t-12,0})/6$ is the average representing the half-year before last half-year (H2), the regression coefficients $\beta_{s,\tau}$, for $s = 1, 2$ and $\tau = 0, 1, 2, 3$, correspond to $x^{(s)}_{j,t,\tau}$ and are pooled over all 24 regions, $c_{i,j,t+12}$ is the forward-looking variable of the consumer price index (CPI), consisting of 8 groups assigned to each individual food item as described in Section 3.1, with regression coefficient ϕ and is fully pooled, and $\epsilon_{i,j,t}$ is the noise term with mean zero, variance σ^2_ϵ and independently distributed across all product i, region j and time t.

The panel data model in (2) can be estimated using standard fixed effect estimation methods. The key explanatory variable $x^{(s)}_{j,t,0}$ takes the value of zero in the absence of disasters in the month associated with time t and in region j. The panel data analysis can therefore be interpreted as a *difference-in-differences* implementation where $\beta^{(s)}_{s,0}$ captures the average effect of disasters on prices by comparing the differences between affected and unaffected regions, while accounting for the differences within regions. We further take into account events that took place in previous months as we can expect effects to endure over a longer time period. For example, rainfalls can damage the local infrastructure which need some time to get repaired. A malfunctioning infrastructure can have much effect on the economy, for consumers and businesses, and therefore on local prices of food. We pool these past events into totals of events of the last three months (Q1), of the three months before Q1 (Q2) and of the last six months before Q1 and Q2 (H2). We also control for demand expectations which are captured in the consumer price index (CPI), denoted by $c_{i,j,t+12}$. The modern monetary theory suggests that prices are set in advance (GalÃ, 2010), given that producers attempt to predict future demand fluctuations. As discussed in Section 3.1, we have eight CPI groups that are assigned to each individual food item: Fruit (Banana, Lemon, Orange and Papaya), Sugar, Oil, Meat (Chicken), Milk & Eggs (Milk and Egg), Tubers (Potato), Vegetables (Carrot, Garlic and Onion) and Rice. Finally, $\epsilon_{i,j,t}$ the disturbance term is assumed to be homoskedastic, it has zero mean and constant variance $\sigma^2_\epsilon > 0$.

4.2 Disentangling demand versus supply effects

We introduce production information in equation (2) to account for supply shocks; see Kilian (2009). For this purpose, we formulate a system of equations in order to disentangle the demand and supply effects. Similar strategies based on systems of demand and supply equations have been widely utilized in microeconometrics; see, for example, Zoutman et al. (2018). When estimation results show significant effects on prices after controlling for production, while significant effects related to production also appear, we infer that disasters affect prices through the supply channel. Otherwise, there are demand-specific shocks that play an important role to understand the effects of disasters on prices. Specifically, the system of equations is determined as follows:

$$\log p_{i,j,t} = \mu_{i,j}^{(p)} + \gamma_{i,t}^{(p)} + \theta_t^{(p)} + \sum_{\tau=0}^{3} \omega_\tau^{(p)} \log q_{i,j,t,\tau} + \sum_{s=1}^{2}\sum_{\tau=0}^{3} \beta_\tau^{(p,s)} x_{j,t,\tau}^{(s)} + \phi^{(p)} \log c_{i,j,t+12} + \epsilon_{i,j,t}^{(p)},$$

$$\log q_{i,j,t} = \mu_{i,j}^{(q)} + \gamma_{i,t}^{(q)} + \theta_t^{(q)} + \sum_{\tau=1}^{3} \omega_\tau^{(q)} \log p_{i,j,t,\tau} + \sum_{s=1}^{2}\sum_{\tau=0}^{3} \beta_\tau^{(q,s)} x_{j,t,\tau}^{(s)} + \phi^{(q)} \log Y_{i,j,t} + \epsilon_{i,j,t}^{(q)}, \quad (3)$$

where the same notation is adopted as for the LSDV model in equation (2), with product $i = 1, \ldots, 14$, region $j = 1, \ldots, 24$, and monthly time index $t = 1, \ldots, 192$, index τ refers to the periods current ($\tau = 0$), Q1 ($\tau = 1$), Q2 ($\tau = 2$) and H2 ($\tau = 3$), where $p_{i,j,t}$ and $q_{i,j,t}$ represent prices and production levels, respectively, and $Y_{i,j,t}$ is the product's yearly crop yield, and $c_{i,j,t+12}$ is the forward-looking consumer price index (CPI). The crop yield is subject to weather and disaster conditions since changes in crop yield can lead to either over or under-production during the season. Also, the instantaneous effect of log-price at time t on log-production at time t is excluded in the model, hence, we start at $\tau = 1$ rather than $\tau = 0$. Finally, the baseline model equations in (3) assume that the residual series $\epsilon_{i,j,t}^{(q)}$ and $\epsilon_{i,j,t}^{(p)}$ are mutually uncorrelated at all exclusive combinations of i, j, t. This assumption implies that both equations in (3) can be estimated via fixed effects regression methods separately. At a later stage, we relax this assumption for robustness considerations.

Table 4: The rainfall and droughts effects on prices

	Prices, in log			Relative prices, in log		
	All	Semi-durables	Perishables	All	Semi-durables	Perishables
Rainfall	0.0981*	0.158**	0.0546	0.101*	0.163**	0.0554
	(0.0505)	(0.0610)	(0.0761)	(0.0524)	(0.0614)	(0.0780)
Rainfall Q1	0.129	0.150	0.111	0.130	0.154	0.109
	(0.105)	(0.163)	(0.157)	(0.108)	(0.167)	(0.162)
Rainfall Q2	0.288**	0.106	0.409**	0.291**	0.108	0.411**
	(0.137)	(0.143)	(0.174)	(0.139)	(0.151)	(0.176)
Rainfall H2	-0.0201	-0.355	0.208	-0.0241	-0.370	0.210
	(0.184)	(0.275)	(0.222)	(0.189)	(0.280)	(0.228)
Droughts	0.0470	0.107***	0.000926	0.0496	0.111***	0.00220
	(0.0790)	(0.0294)	(0.121)	(0.0820)	(0.0315)	(0.124)
Droughts Q1	0.179*	0.276**	0.0964	0.184*	0.283**	0.0995
	(0.0908)	(0.110)	(0.201)	(0.0965)	(0.110)	(0.207)
Droughts Q2	0.126	0.215**	0.0509	0.131	0.221**	0.0537
	(0.132)	(0.0849)	(0.190)	(0.137)	(0.0888)	(0.197)
Droughts H2	0.453**	0.475*	0.433	0.463**	0.491*	0.438
	(0.189)	(0.259)	(0.409)	(0.204)	(0.258)	(0.425)
log CPI_{t+12}	0.289***	0.255***	0.319***	0.266***	0.229***	0.299***
	(0.0444)	(0.0354)	(0.0695)	(0.0539)	(0.0393)	(0.0773)
Observations	53,322	21,536	31,786	53,322	21,536	31,786
N	336	144	192	336	144	192
Overall R-sq.	0.978	0.984	0.973	0.855	0.902	0.815
Within R-sq.	0.0423	0.0510	0.0396	0.0377	0.0438	0.0364
Hausman test	60.00	80.38	50.61	36.88	32.63	50.33

Robust standard errors in parentheses, with *** p<0.01, ** p<0.05, * p<0.1, and N represents the number of region/product combinations included in the regression. The table includes the regression results for the 14 food items (All column), as well as considering only Semi-durable items (6 products), and Perishable items (8 products). The panel regressions include 168 monthly time effects, while the number of product time-varying effects varies by grouping, 2,352 for the all items regression, while 1,344 and 1,008 fixed effects for the Semi-durable and Perishable items regression respectively unless missing information. Standard errors are clustered at regional level. The Chi2 statistic is reported for the Hausman test.

4.3 Empirical results

The main results are reported in Table 4. The first three columns report the effects on prices, while the last three columns report the effects on relative prices. In both specifications, the Hausman-Wu-Durbin test statistic is presented at the bottom of this Table. This χ^2 statistic shows that model parameters are adequately captured by a fixed effects regression, see Davidson and MacKinnon (1990) for further details on the test implementation. The overall and within coefficients of determination (R^2) are also reported for both specifications and they show rather different values. The overall R^2 is measured for all fitted values of the dependent variable based on the fixed effect regression estimates using the original predictor variables. Hence, this R^2 is based on many (noisy) data points. The within R^2 is based on mean variations (to allow for the presence of fixed effects) which are less noisy relative to the original data. Hence we observe major differences between the two R^2 values. To verify the stationary behaviour of the data in the time dimension, we have computed the augmented Dickey-Fuller (ADF) test statistic for panel data as described in Choi (2001). The ADF test statistic strongly rejects the null hypothesis of unit root (non-stationarity) for all residual terms; see Table 5. The individual ADF (Dickey and Fuller, 1979) and Phillips-Perron (Phillips and Perron, 1988) tests for each city/product time series also reject the null hypothesis of the presence of a unit root in the time series; see Figure 1 for a graphical display of all city/product time series. We can conclude from these unit root test statistics that the regression results presented below are not spurious.

Table 5: Augmented Dickey-Fuller test for panel data, statistics

	log price, residual		log rel. price, residual	
	w.o/ trend	w/ trend	w.o/ trend	w/ trend
Inverse chi-squared (668)	6107.4	5680.3	6067.4	5644.3
Inverse normal	-60.8	-58.3	-60.6	-58.1
Inverse logit t (1674)	-91.5	-85.0	-90.8	-84.4
Modified inv. chi-squared	148.8	137.1	147.7	136.1

The table reports the statistic associated to the Augmented Dickey-Fuller test, the inverse chi-squared test has 2*N degree of freedom, where N is the number of product/region combinations, equal to 334 due that one product has insufficient observations for the test, and the inverse logit t has 5*N +4 degree of freedom, equal to 1,674. The null hypothesis is given by All panels contain unit root, while the alternative hypothesis by At least one panel is stationary.

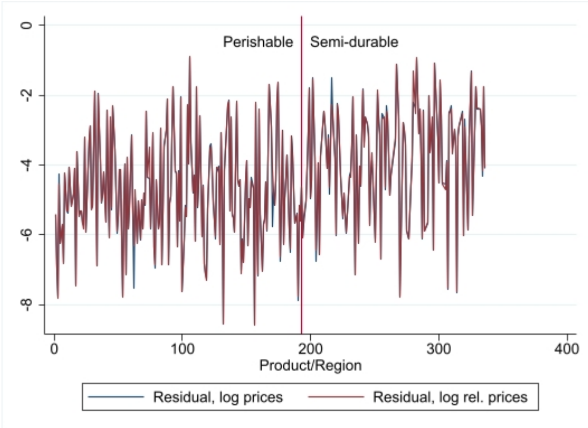
The regression results show that both rainfalls and droughts significantly affect prices. While rainfalls are estimated to contemporaneously and after four to six months (Q2) affect prices, droughts are estimated to affect prices after one to three months (Q1) and after half year (H2). These effects vary depending on whether the events affect semi-durable or perishable products. Prices of perishable products are only affected by rainfalls during Q2, while those of semi-durable products are affected by both rainfalls and droughts, with the latter affecting prices from more than a year ago. Rainfalls increase prices of semi-durable product instantaneously. The results imply the predictions that a one standard deviation increase in the number of people being affected by rainfalls, increases the price of perishable products by 0.46 percent during Q2, and 0.18 percent at once for semi-durable products. Meanwhile, such an increase in the number of affected people due to droughts, is expected to increase the price of semi-durable products at once by 0.12 percent, and 1.52 percent in H2. These findings are robust to the use of relative prices instead of actual price levels. The advantage of using relative prices is that they implicitly account for unobserved seasonal factors and possibly for cost variables, such as fuel and energy prices, which are arguably similar across regions.

The regression results in Table 4 do not confirm the *customer anger* hypothesis of Cavallo et al. (2014) in the short-run (though we do not analyze the price equilibrium effects in the long-run). The impact of price increases due to rainfalls is short-lived, given that all estimates associated with lagged variables beyond six months are not significant. However, the impact of price increases due to drought events has a longer duration. This finding is consistent with the recent evidence provided by Klomp (2020); Heinen et al. (2019); Parker (2018) where they use aggregated consumer price indexes across developed and developing countries.

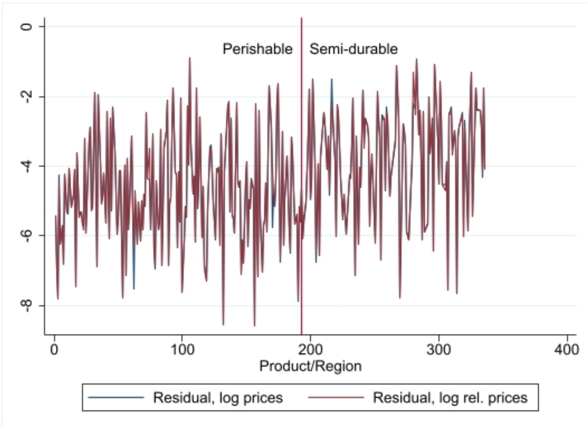
In Table 6 we present the results for the system of equations in (3). The first three columns report the result for the price equation, while the latest three column are for production. We also report the Durbin-Wu-Hausman test statistics (Davidson and MacKinnon, 1990) at the bottom of Table 6. The χ^2-statistic for the Durbin-Wu-Hausman test shows that the model parameters are adequately captured by fixed effects regressions except for

Figure 1: Individual unit-root tests

(a) Augmented Dickey-Fuller



(b) Phillip-Perron



The figure summarizes the associated t-statistic to the Augmented Dickey-Fuller and Phillip-Perron test for each regional/product combination (336 series), respectively. The null hypothesis is given by The series follows a random walk process without drift, and the critical values are determined at -3.49, -2.89 and -2.58 for the 1, 5, and 10 percent significant levels. The red line divides perishable from semi-durable products.

the price equation for semi-durable products. The price equation controls for production variables, and vice-versa. The relationship between prices and production is negative as it clearly should be. Higher production leads to lower prices. Noticeably, there is no longer significant effects of either droughts or rainfalls on prices when production controls are present in the model. Meanwhile, both rainfall and drought events have estimated coefficients which imply the reduction of production quantities. While rainfalls show a reduction in the production of semi-durable and perishable products, droughts only show a reduction in the production of perishable products. These results are confirmed by using relative prices and production, see Table 9 in the Appendix. From these findings we can conclude that disasters affect prices via the supply channel.

Our results contribute to a growing literature aimed at quantifying the economic effects of climate change. El Niño Southern oscillations (ENSO) reduce the global production of maize, rice, and wheat (Iizumi et al., 2014), as well as the overall production of cereal (Dorosh et al., 2016). Likewise, droughts and extreme heat often reduce cereal production through both harvested area and yields (Lesk et al., 2016). Meanwhile, recent evidence suggests that the inter-temporal demand preferences for consuming tomorrow instead of today remained unaffected after the occurrence of natural disasters (Akesaka, 2019). Indeed, the affected individuals are expected to become more patient after such events (Hanaoka et al., 2018), which makes less likely to attribute a price increases to impatient consumers. To the best of our knowledge, this paper is the first documenting the effects of natural disasters on both prices and production within the controlled institutional environment of a single country. Therefore, allowing to properly disentangle the mechanism through which a disaster increases prices.

Finally, our results show that the reduction in production dominates over the increase in prices. For instance, one standard deviation increase in the percentage of people affected by rainfalls leads to an average price increase of 0.46 percent for perishable products, while it leads to a 3.11 percent decline on the production of those products. Therefore, the associated gross income (production times prices) declines, which mask the increase on prices. The gross income decline due to disasters is consistent with the discussions in the macroeconomic literature; see, for example, Tol (2009) for a comprehensive review. In our analysis based on a data set with a high granularity level, we can confirm that more rainfalls will lead to income declines but will also attribute to production declines which are much stronger than associated price increases.

Table 6: The rainfall and droughts effects on prices and production

	Y = log Prices, X= log Production			Y = log Production, X = log Prices		
	All	Semi-durables	Perishables	All	Semi-durables	Perishables
X	-0.00813**	-0.00447**	-0.0110*			
	(0.00324)	(0.00206)	(0.00636)			
X-3	-0.0145***	-0.00715	-0.0186***	-0.109	-0.184	-0.0825
	(0.00376)	(0.00526)	(0.00502)	(0.156)	(0.287)	(0.173)
X-6	0.00331	0.00888*	0.00391	0.800***	1.488***	0.584**
	(0.00508)	(0.00500)	(0.00752)	(0.209)	(0.452)	(0.214)
X-12	0.00409	0.0103	0.00740	-0.937***	-1.421***	-0.783***
	(0.00651)	(0.0114)	(0.00745)	(0.217)	(0.458)	(0.227)
Rainfall	0.0613	0.240	0.0350	-0.133	-6.275**	1.289
	(0.0826)	(0.204)	(0.0834)	(1.082)	(2.945)	(1.039)
Rainfall Q1	-0.0286	-0.0419	-0.0221	0.163	1.418	-0.219
	(0.160)	(0.583)	(0.148)	(1.646)	(3.674)	(1.469)
Rainfall Q2	0.343*	0.674	0.266	-2.140**	-0.214	-2.749***
	(0.192)	(0.681)	(0.183)	(0.778)	(2.737)	(0.755)
Rainfall H2	-0.106	-0.642	-0.0601	-1.919	-7.974	-0.231
	(0.304)	(1.276)	(0.286)	(1.620)	(5.004)	(2.385)
Droughts	-0.0342	-0.0371	-0.0335	0.177	-1.254	0.403
	(0.0751)	(0.184)	(0.0864)	(0.569)	(1.457)	(0.888)
Droughts Q1	-0.126	-0.651	-0.0968	-0.422	-2.837	0.0589
	(0.165)	(0.826)	(0.202)	(1.908)	(2.514)	(2.136)
Droughts Q2	-0.185	0.0107	-0.209	-2.265**	0.278	-2.852***
	(0.137)	(0.524)	(0.132)	(0.977)	(1.773)	(0.859)
Droughts H2	-0.120	0.0775	-0.141	-1.974	-2.515	-1.819
	(0.286)	(1.165)	(0.289)	(1.367)	(7.702)	(1.745)
log Z	0.319***	0.291***	0.327***	0.824***	0.936***	0.810***
	(0.0639)	(0.0782)	(0.0719)	(0.0792)	(0.130)	(0.0842)
Number of obs	29,389	5,401	23,988	36,731	9,578	27,153
N	214	55	159	274	88	186
Overall R-sq.	0.978	0.975	0.978	0.908	0.849	0.936
Within R-sq.	0.0569	0.0941	0.0526	0.0631	0.0294	0.114
Hausman test	116.87	44.7	97.5	341.91	462.95	215.03

Robust standard errors in parentheses, with $***\ p$ <0.01, $**\ p$ <0.05, $*\ p$ <0.1, and N represents the number of region/product combinations included in the regression. The table includes the regression results for the 14 food items (All column), as well as considering only Semi-durable items (6 products), and Perishable items (8 products). The panel regressions include 168 monthly time effects, while the number of product time-varying effects varies by grouping, 2,352 for the all items regression, while 1,344 and 1,008 fixed effects for the semi-durable and perishable items regression respectively unless missing information. Standard errors are clustered at regional level. The Hausman test is a χ^2 distributed, with the number of degree of freedom determined by the matrix rank of the variance of the difference between the coefficients of the fixed and random effects estimators. The variable Z stands for CPI_{t+12} in the price regressions and for crop yield in the production regressions.

4.4 Robustness to regional and product heterogeneity

A potential shortcoming of the model in equation (2) is its implied homogeneous response of disasters on prices. Hence, the model ignores the regional and product differences which could emerge due to preparedness capacity. We therefore enable a more general formulation of the model that allows for variability across regions and products in the average response β. Specifically, we consider the more general model specification given by the equations

$$\begin{aligned} \log p_{i,j,t} &= \tau_{i,j} + \gamma_i + \theta_t + \sum_{s=1}^{2}\sum_{\tau=0}^{3} \alpha_{i,j,\tau}^{(s)} x_{j,t,\tau}^{(s)} + \phi \log c_{i,j,t+12} + \epsilon_{i,j,t}, \\ \tau_{i,j} &= \mu_{i,j} + \upsilon_{i,j}, \\ \alpha_{i,j,\tau}^{(s)} &= \beta_{\tau}^{(s)} + u_{i,j,\tau}^{(s)}, \end{aligned} \tag{4}$$

where the same notation is used as in model equation (2), and additionally, where $\upsilon_{i,j}$ and $u_{i,j,\tau}^{(s)}$ are random variables with zero mean and constant standard deviation, σ_υ and σ_u respectively. These two random variables are assumed to be uncorrelated with $\epsilon_{i,j,t}$, for all i, j, t, while there is also no correlation between regions and across events. In this setting, $\mu_{i,j}$ and $\beta_{\tau}^{(s)}$ are still regarded as fixed, while $\upsilon_{i,j} + u_{i,j,\tau}^{(s)} x_{j,t,\tau}^{(s)}$ are time-varying random effects to allow for heterogenous effects of disasters on prices. Hence, for this model specification, the effects of disasters can vary across products. We notice that for the model extension above, we only consider product fixed effects instead of the time-varying version in the model of the previous section, in order to avoid parameter identification issues. This extension of the model is not new and is known in the literature as multilevel and/or hierarchical linear models; see, for example, Mcculloch and Neuhaus (2014) for a review of the necessary modifications for parameter estimation.

The estimation results are summarized in Table 7. There are significant effects on prices from both rainfalls and droughts. The price of perishable products is affected by rainfalls, while the semi-durable price is affected by both rainfalls and droughts. Similar from Table 4, we find that rainfalls affect perishable prices after four to six months (Q2), while droughts affect prices of semi-durable products only after one to six months (Q1 and Q2). Also, the estimates show that rainfalls also affect the prices of semi-durable products in Q1 and Q2.

Table 7: The rainfall and droughts effects on prices via multilevel mixed-effects linear regression using the method of maximum likelihood estimation.

	Prices, in log		
	All	Semi-durables	Perishables
Rainfall	0.0297	-0.0758	0.0986
	(0.0986)	(0.132)	(0.135)
Rainfall Q1	0.359	0.662*	0.151
	(0.266)	(0.370)	(0.366)
Rainfall Q2	0.732***	0.775**	0.701*
	(0.280)	(0.327)	(0.416)
Rainfall H2	-0.0285	-1.066	0.681
	(0.401)	(0.683)	(0.474)
Droughts	0.0600	0.0536	0.0505
	(0.0537)	(0.0693)	(0.0789)
Droughts Q1	0.318*	0.391*	0.251
	(0.179)	(0.230)	(0.252)
Droughts Q2	0.320**	0.563***	0.123
	(0.158)	(0.190)	(0.221)
Droughts H2	0.412	0.277	0.492
	(0.293)	(0.414)	(0.407)
log CPI_{t+12}	0.446***	0.409***	0.480***
	(0.0276)	(0.0372)	(0.0416)
Number of obs	53,324	21,538	31,786
N	336	144	192
LogLik	11,368.7	2,421.9	9,473.3

Robust standard errors are presented in parentheses, with $***$ p <0.01, $**$ p <0.05, $*$ p <0.1, and N represents the number of region/product combinations included in the regression. The regression results are presented for all 14 product items ("All"), as well as considering only semi-durables (6 products) and perishables (8 products). The panel regressions include 168 monthly time effects, while the number of item fixed effects varies by grouping, 14 for the All items regression, while 6 and 8 fixed effects for the semi-durables and perishables items regressions, respectively. The (pseudo) maximized Log-Likelihood ("LogLik") value is reported for each regression.

4.5 Robustness to correlated residuals

The estimation of the parameters in the demand and supply equations in (3) assumes that both residual terms, $\epsilon^{(p)}_{i,j,t}$ and $\epsilon^{(q)}_{i,j,t}$, are uncorrelated. However, unobservable factors such as product or land quality as well as market structure variables, could affect both equations simultaneously, thus leading to inefficient estimates of model parameters in (3).

To overcome the potential efficiency issue, we consider a simplistic approach that allows for a simultaneous correlation between $\epsilon^{(p)}_{i,j,t}$ and $\epsilon^{(q)}_{i,j,t}$. Such model is typically know as the Seemingly Unrelated Regression (SUR) method (Zellner, 1962). Specifically, we consider the following error covariance matrix

$$\Omega_j = \mathrm{Var}(\epsilon^{(q)}_{i,j,t}, \epsilon^{(p)}_{i,j,t}), \qquad \text{for all } i, t, \text{in a given } j \tag{5}$$

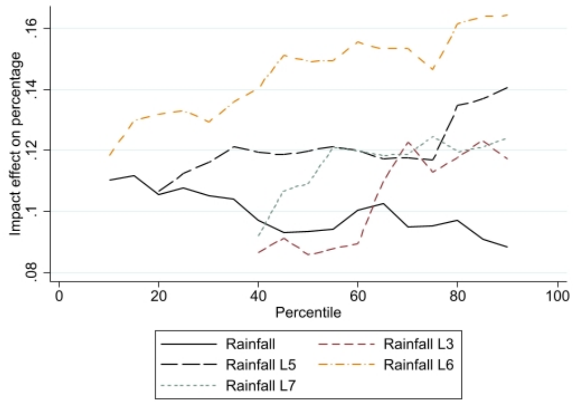
where Ω_j is an unknown non-singular matrix that needs to be estimated. Therefore, we proceed to estimate the parameters in the system of equations (3), together with Ω_j, via the feasible generalized least squares (FGLS) method. The FGLS method is a two-step approach, where the residuals of the independent regressions in (3) are used to compute the elements of Ω_j. In a second step, we consider a generalized least squares regression to compute the parameters of the model, see for instances Srivastava and Dwivedi (1979) for a summary of SUR methods.

The estimation results are presented in Table 10 of the appendix section. The Breusch-Pagan test statistic is presented at the bottom of the table. The χ^2 statistic shows that we can reject the hypothesis that the correlation between residual terms is zero but for semi-durable products. The first three columns report the results for the price equations, while the last three columns report those for production. The reported estimation results in Table 10 confirm the results reported in Tables 6 and 9, and indicate a negative relationship between prices and production. Likewise, after controlling for production, we do not find significant effects of either rainfalls or droughts on the price of semi-durable products, while still one positive effect of Rainfalls Q2 on the price of perishable. Meanwhile, rainfalls negatively affect the production of both semi-durable and perishable products.

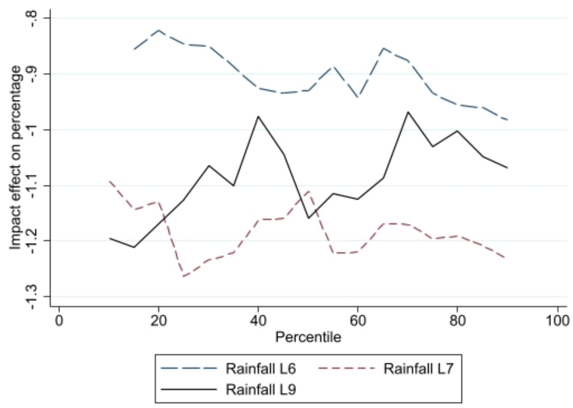
Overall, the results confirm the existence of a supply channel mechanism that is able to explain the price increases in Table 4, and in particular for semi-durable products.

Figure 2: The impact of rainfalls events across different intensity

(a) Prices



(b) Production and value-added



The figure plots the significant β_l coefficients associated to rainfall events as estimated from the 10th to the 90th percentile, with the standard errors clustered at regional level. The percentiles are estimated based on the severity of the rainfall events in each region.

4.6 The role of extreme events

The macroeconomic literature highlights the importance of extreme events to uncover the negative impacts of disasters on economic growth. Indeed, most empirical evidence only analyze major events such as earthquakes or storms; see, for example, Cavallo et al. (2013); Fomby et al. (2013). So far we have extensively given evidence of a decline in production and an increase in price after a disaster event has taken place. Overall, the decline in Peruvian gross domestic product could mask these two opposite forces. To verify the role of extreme events in our analysis, we analyze the distributional impacts of disasters by grouping them into percentiles. In effect, we estimate the basic regressions as implied by model equation (2) for prices and production by considering the set of rainfall events that are above the q-percentile. We only consider only rainfall events due to data availability as we need sufficient observations to classify observations events into percentiles. Rainfall events occur much more frequently than drought events in Peru overall. Furthermore, we do not group lagged rainfall events (contemporaneous, Q1, Q2 and H2) because each event needs to be classified according to its magnitude (imposed by a specific quantile). When we then average the events after such classifications over time, the associated severity of the impact can be either overestimated or underestimated. We therefore consider the regression equation (2) but with monthly lags up to a year (L1, L2, . . ., L12).

The results are summarized in Figure 2. We only plot the estimated coefficients with corresponding p-values below 0.10. Panel (a) presents the results for prices and panel (b) for production. A key finding is that as we increase the percentile, the impact of rainfalls become more severe. The contemporaneous impact of rainfalls on prices decline with the severity of the disaster, while the opposite for the delayed effects (Rainfall L3, L5, L6, and L7). Hence we find that higher price increases occur after more extreme events. Similarly, we observe a stronger decline on production associated to the severity of the events (Rainfall L6 and L7), although the opposite happens after nine months (Rainfall L9).

We can conclude that the negative macroeconomic effect during extreme events can be explained by the decline of production. Nevertheless, the contemporaneous increase on prices could easily, partially, offset the decline in production during moderate or less severe events. In the extreme case of no delayed effects on either prices or production, the simple contemporaneous increase on prices could misguidedly lead to conclude that the gross domestic product in Peru increases during the occurrence of moderate disasters events.

5 Conclusions

In this study we have considered the effects of two natural disasters, intense rainfalls and droughts, on prices and production for fourteen food products in twentyfour regions in Peru. By analyzing the data at this high granularity level, we have been able to address two key empirical shortcomings in similar macroeconomic studies: (*i*) data aggregation, and (*ii*) counterfactual biases. First, our detailed sub-national price and production information in the data set allows us to disentangle real from nominal effects, while accounting for within-country differences. Second, the large variety of regions in Peru, coupled with the random nature of climate events, allows us to establish a natural counterfactual for each event by comparing prices and production between unaffected and affected regions in Peru, and even within regions.

Our empirical results strongly indicate that the disaster events of rainfalls and droughts increase prices and reduce production levels at the same time. The disaster effects vary conditional on the storage life duration of the products. Perishable products are affected only by rainfalls, while both disasters affect semi-durable products. The price increases due to rainfall is short-lived, while droughts effects have a longer duration. The price increase can mainly be explained by the decline in production which indicate that the supply channel is the main mechanism through which disasters affect prices. Notably, the decline in production is stronger during extreme events, albeit the increase in prices.

These empirical findings and conclusion remain when we allow for regional and product heterogeneity, when we consider correlated unobservable factors that explain both prices and production, and when we recursively estimate the individual monthly effects of disasters over time.

Statements and Declarations

The authors have no financial or non-financial interests that are directly or indirectly related to the research work conducted for this paper.

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A Additional Tables

Table 8: Relationship between climate factors and disaster-affected populations, yearly frequency

	Precipitation, ratio		Temperature, ratio	
	OLS	FE	OLS	FE
People aff. by rainfalls	4.764***	5.756***		
	(1.795)	(1.993)		
People aff. By droughts			0.0475	0.168**
			(0.0656)	(0.0750)
Population ratio	0.0245	0.303	0.00195	0.0443
	(0.0239)	(0.285)	(0.00283)	(0.0665)
N. of habitans x doctor	4.28e-05	0.000218***	1.07e-05*	2.55e-05*
	(3.56e-05)	(6.11e-05)	(5.37e-06)	(1.35e-05)
Observations	343	343	70	63
N		24		21
Overall R-sq	0.3183	0.3601	0.4251	0.6469
Within R-sq		0.1854		0.2916

Robust standard errors in parentheses, with $***$ p <0.01, $**$ p <0.05, $*$ p <0.1, and N represents the number of regions included in the regression. The regression analysis uses annual data on climate-related factors such as precipitation (in millimeters) and average temperature (in degrees Celsius), with the number of people affected by disasters aggregated yearly from monthly data, climate variables expressed as ratios relative to historical averages per region, and the number of individuals impacted by rainfall and droughts presented as a percentage of the total population, while the population ratio indicates the percentage of the population per region and the number of habitants per doctor reflects the average number of individuals served by each doctor. Finally, OLS stands for Ordinary Least Square, and FE for Fixed Effects Panel Data regressions.

Table 9: The rainfall and droughts effects on prices and production, in relative terms

	Y = log rel. Prices, X= log rel. Production			Y = log rel. Production, X = log rel. Prices		
	All	Semi-durables	Perishables	All	Semi-durables	Perishables
X	-0.00842**	-0.00514**	-0.0114*			
	(0.00323)	(0.00240)	(0.00621)			
X-3	-0.0141***	-0.00952	-0.0175***	-0.123	-0.172	-0.107
	(0.00374)	(0.00562)	(0.00498)	(0.158)	(0.280)	(0.180)
X-6	0.00358	0.00634	0.00482	0.823***	1.431***	0.630**
	(0.00490)	(0.00551)	(0.00717)	(0.215)	(0.427)	(0.235)
X-12	0.00332	0.00541	0.00671	-0.936***	-1.395***	-0.788***
	(0.00631)	(0.0127)	(0.00713)	(0.228)	(0.444)	(0.247)
Rainfall	0.0644	0.227	0.0390	-0.186	-6.433**	1.263
	(0.0849)	(0.211)	(0.0862)	(1.080)	(2.958)	(1.041)
Rainfall Q1	-0.0361	-0.117	-0.0232	-0.00680	0.722	-0.249
	(0.163)	(0.582)	(0.151)	(1.669)	(3.882)	(1.479)
Rainfall Q2	0.343*	0.634	0.269	-2.329**	-0.829	-2.809***
	(0.194)	(0.675)	(0.188)	(0.871)	(3.079)	(0.828)
Rainfall H2	-0.113	-0.760	-0.0518	-1.986	-7.920	-0.329
	(0.313)	(1.265)	(0.292)	(1.629)	(5.229)	(2.411)
Droughts	-0.0307	0.00344	-0.0326	0.154	-1.250	0.379
	(0.0807)	(0.182)	(0.0895)	(0.564)	(1.475)	(0.879)
Droughts Q1	-0.116	-0.600	-0.0938	-0.429	-2.918	0.0780
	(0.175)	(0.858)	(0.207)	(1.909)	(2.555)	(2.145)
Droughts Q2	-0.178	0.0550	-0.206	-2.264**	0.222	-2.830***
	(0.148)	(0.581)	(0.137)	(0.987)	(1.840)	(0.883)
Droughts H2	-0.103	0.316	-0.135	-2.038	-2.747	-1.865
	(0.316)	(1.297)	(0.302)	(1.410)	(7.929)	(1.768)
log Z	0.290***	0.240**	0.308***	0.819***	0.914***	0.805***
	(0.0779)	(0.103)	(0.0795)	(0.0761)	(0.136)	(0.0832)
Number of obs	29,389	5,401	23,988	36,731	9,578	27,153
N	214	55	159	274	88	186
Overall R-sq.	0.863	0.937	0.822	0.893	0.747	0.938
Within R-sq.	0.0508	0.0718	0.0488	0.0607	0.0278	0.112
Hausman test	146.94	39.91	94.85	277.96	427.06	56.97

Robust standard errors in parentheses, with $***$ p <0.01, $**$ p <0.05, $*$ p <0.1, and N represents the number of region/product combinations included in the regression. The regression results are presented for all 14 product items ("All"), as well as considering only semi-durables (6 products) and perishables (8 products). The panel regressions include 168 monthly time effects, while the number of item fixed effects varies by grouping, 14 for the All items regression, while 6 and 8 fixed effects for the semi-durables and perishables items regressions, respectively. The variable Z stands for CPI_{t+12} in the price regressions and for crop yield in the production regressions.

Table 10: The rainfall and droughts effects on prices and production using the Seemingly Unrelated Regression (SUR) method.

	Y = log Prices, X= log Production			Y = log Production, X = log Prices		
	All	Semi-durables	Perishables	All	Semi-durables	Perishables
X	-0.00143	-0.00512	0.00223			
	(0.00391)	(0.00312)	(0.00875)			
X-3	-0.00515	-0.00714	-0.00278	-0.310**	-0.482*	-0.337**
	(0.00602)	(0.00808)	(0.0104)	(0.128)	(0.256)	(0.148)
X-6	-0.00334	0.00676	-0.00711	0.765***	1.166***	0.684***
	(0.00511)	(0.00804)	(0.00855)	(0.141)	(0.278)	(0.175)
X-12	-0.00321	0.0117	-0.0107	-0.652***	-0.851***	-0.675***
	(0.00822)	(0.0163)	(0.0104)	(0.116)	(0.200)	(0.181)
Rainfall	-0.113	-0.120	-0.0999	-0.514	-3.788***	0.227
	(0.0847)	(0.310)	(0.0800)	(0.531)	(1.318)	(0.639)
Rainfall Q1	-0.270	-0.476	-0.207	0.0350	6.092	-1.284
	(0.170)	(0.641)	(0.165)	(2.085)	(4.552)	(1.487)
Rainfall Q2	0.645***	1.078	0.617***	0.121	7.311*	-1.173*
	(0.229)	(0.671)	(0.223)	(1.178)	(3.790)	(0.609)
Rainfall H2	-0.240	-0.314	-0.164	-2.319	-17.85***	-0.0236
	(0.397)	(1.844)	(0.298)	(1.805)	(6.555)	(1.792)
Droughts	-0.0226	0.350	-0.0594	-0.132	-2.382	-0.0470
	(0.0945)	(0.385)	(0.0899)	(0.391)	(1.878)	(0.548)
Droughts Q1	-0.157	-0.367	-0.154	-0.276	2.785	-0.361
	(0.170)	(1.330)	(0.174)	(1.741)	(3.068)	(1.744)
Droughts Q2	-0.210	-0.484	-0.194	-0.226	18.63***	-1.221
	(0.136)	(0.789)	(0.125)	(1.892)	(3.798)	(1.152)
Droughts H2	-0.00393	0.774	-0.0669	-1.999*	-15.74**	-1.538
	(0.334)	(1.921)	(0.295)	(1.209)	(7.638)	(1.452)
Z	0.261***	0.198***	0.329***	0.515***	1.233***	0.501***
	(0.0378)	(0.0428)	(0.0597)	(0.0626)	(0.159)	(0.0613)
Observations	27,644	5,097	22,547	27,644	5,097	22,547
Breusch-Pagan test	5.484	0.514	16.976	5.484	0.514	16.976

Robust standard errors in parentheses, with $***$ p <0.01, $**$ p <0.05, $*$ p <0.1. The regression results are presented for all 14 product items ("All"), as well as considering only semi-durables (6 products) and perishables (8 products). The panel regressions include 168 monthly time effects, while the number of item fixed effects varies by grouping, 14 for the All items regression, while 6 and 8 fixed effects for the semi-durables and perishables items regressions, respectively. The χ^2 statistic for the Breusch-Pagan test is reported for each regression. The variable Z stands for CPI_{t+12} in the price regressions and for crop yield in the production regressions.